Journal of Systems Engineering and Electronics
Vol. 32, No. 6, December 2021, pp.1338 – 1344

Bayesian track-before-detect algorithm for nonstationary sea clutter

XU Cong[1,*], HE Zishu[1], LIU Haicheng[2], and LI Yadan[3]

1. Department of Information and Communication, University of Electronic Science and Technology of China, Chengdu 610051, China; 2. Department of Electrical and Information Engineering, Heilongjiang Institute of Engineering, Harbin 150026, China; 3. College of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: Radar detection of small targets in sea clutter is a particularly demanding task because of the nonstationary characteristic of sea clutter. The track-before-detect (TBD) filter is an effective way to increase the signal-to-clutter ratio (SCR), thus improving the detection performance of small targets in sea clutter. To cope with the nonstationary characteristic of sea clutter, an easily-implemented Bayesian TBD filter with adaptive detection threshold is proposed and a new parameter estimation method is devised which is integrated into the detection process. The detection threshold is set according to the parameter estimation result under the framework of information theory. For detection of closely spaced targets, those within the same range cell as the one under test are treated as contribution to sea clutter, and a successive elimination method is adopted to detect them. Simulation results prove the effectiveness of the proposed algorithm in detecting small targets in nonstationary sea clutter, especially closely spaced ones.

Keywords: small target, track-before-detect (TBD), nonstationary sea clutter, closely spaced target.

DOI: 10.23919/JSEE.2021.000113

1. Introduction

Radar detection of small targets in sea clutter is a pressing problem in both military and civilian domains. The varying characteristics of sea clutter make the detection of small targets extremely challenging [1]. Existing detection methods include the knowledge-aided methods [2], feature-based detectors [3], sparse separation methods [4] and many others [5–8]. Recently, the track-before-detect (TBD) filter has become very popular and widely used in radar target detection. There exist three main kinds of TBD filters, namely histogram probablistic multi-hypothesis tracker (H-PMHT), dynamic-programming based TBD (DP-TBD), and recursive Bayesian TBD. In [9], a computationally efficient DP-TBD algorithm was proposed to detect targets by GNSS-based passive radar. In [10], a TBD algorithm that used particle filters was applied to detect targets on the sea. In [11], a Bernoulli TBD filter was adopted to detect small targets in K-distributed sea clutter. In [12], comparisons of detection performances between H-PMHT, Bernoulli filter and multi-Bernoulli filter were provided, and the results showed that none of these filters could be useful in K-distributed clutter. It is proved that the recursive Bayesian TBD is preferable to be applied to all target types and clutter distributions [13]. However, none of these cases concerns the nonstationarity of sea clutter. In [14], Bernoulli TBD filter was developed to detect both widely separated and closely spaced targets on the sea.

In this paper, a new Bayesian TBD filter for small target detection in nonstationary sea clutter is proposed. The main contributions are as follows. First, the proposed algorithm can adapt to sea clutter changes by integrating clutter parameter estimation into a detection process. Nonstationary sea clutter can be regarded as piecewise stationary series in the minimax optimality. Second, adaptive detection threshold is assigned by using the logistic loss function to combat false alarms. Third, closely spaced targets lying in the same cell of the measurement map can be distinguished. The remaining part of this paper is organized as follows. In Section 2, a detailed description of the new proposed algorithm is given. Simulation results and conclusions are shown in Section 3 and Section 4 respectively.

2. Proposed algorithm

Suppose there are multiple Swerling 0 targets in K-distributed sea clutter and only one sample per measurement cell is available. For the sake of simplicity, one-dimension range measurement is considered in this study. Range domain D is divided into L resolution cells, each of which covers an area ΔA_l. It is assumed that there is at most one target in each range cell. Also, the intensity of

Manuscript received October 28, 2020.
*Corresponding author.
This work was supported by the National Natural Science Foundation of China (61671139).

all range cells at time k is denoted as z_k, while the target state is denoted as $\boldsymbol{x}_k = \left[r \ \dot{r} \ A_k\right]^{\mathrm{T}}$, where r, $\dot{r}$, and A_k represents range, range rate, and the amplitude of the target signal respectively [15].

2.1 Bayesian TBD filter

The grid-based approach is adopted for the implementation of Bayesian TBD filter. Applying (3.11) to (3.14) of [16], we get

$$p(\boldsymbol{x}_k|z_k) = \frac{L(z_k|\boldsymbol{x}_k)\,p(\boldsymbol{x}_k)}{\int_D L(z_k|\boldsymbol{x}_k)\,p(\boldsymbol{x}_k)\mathrm{d}\boldsymbol{x}_k} \tag{1}$$

where $L(z_k|\boldsymbol{x}_k)$ denotes the likelihood function, $p(\boldsymbol{x}_k)$ is the prior density, $p(\boldsymbol{x}_k|z_k)$is the prosterior density, and D is the target state space.

Then the continuous location state space is transitioned to discrete cell-based state space by integrating (1) over the area of the lth resolution cell,

$$p_l(\boldsymbol{x}_k|z_k) = \int_{\Delta A_l} p(\boldsymbol{x}_k|z_k)\mathrm{d}\boldsymbol{x}_k = \frac{\int_{\Delta A_l} L(z_k|\boldsymbol{x}_k)\,p(\boldsymbol{x}_k)\mathrm{d}\boldsymbol{x}_k}{\int_D L(z_k|\boldsymbol{x}_k)\,p(\boldsymbol{x}_k)\mathrm{d}\boldsymbol{x}_k} \tag{2}$$

where ΔA_l is the length of the lth resolution cell.

Since the exact position of a target in a resolution cell is unknown, the probability of the target existence in a certain cell is given by

$$p_{l|z}(\boldsymbol{x}_k|z_k) = \frac{\ell\left(z_k^l\middle|H_k^l\right)p_l(\boldsymbol{x}_k|z_k)}{\sum_{l'}\ell\left(z_k^{l'}\middle|H_k^{l'}\right)p_{l'}(\boldsymbol{x}_k|z_k)} \tag{3}$$

where $\ell\left(z_k^l\middle|H_k^l\right) = \int_{\Delta A_l} L(z_k|\boldsymbol{x}_k)\mathrm{d}\boldsymbol{x}_k$, and l' denotes all the cells in range domain.

Considering target motion, the transition probability density function can be defined as $\pi(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})$. Then, target density can be calculated by

$$p\left(H_k^l\right) = \sum_{l'}\frac{1}{\Delta A_{l'}}\int_{\Delta A_{l'}} P\left(H_{k-1}^{l'}\right)\mathrm{d}\boldsymbol{x}_{k-1}\int_{\Delta A_l}\pi(\boldsymbol{x}_k|\boldsymbol{x}_{k-1})\mathrm{d}\boldsymbol{x}_k = \sum_{l'} p\left(H_{k-1}^{l'}\right)\prod\left(l\middle|l'\right) \tag{4}$$

where $p(H_k^l)$ represents the probability of target existence in cell l, $\prod\left(l\middle|l'\right)$ denotes the transition probability of a target from cell l to cell l'.

Sea clutter is modeled as K-distribution given by

$$p(z_k^l|\eta) = \frac{2z_k^l}{\eta}\exp\left(-\frac{{z_k^l}^2}{\eta}\right), \tag{5}$$

$$p(\eta|\upsilon,b) = \frac{b^{\upsilon}\eta^{\upsilon-1}}{\Gamma(\upsilon)}\exp(-b\eta), \tag{6}$$

where $\Gamma(\cdot)$ denotes the gamma function, υ represents the shape parameter, η refers to the mean square of speckle amplitude, and b is the scale.

Since the mean value of target amplitude A_k is integrated into the state vector, the likelihood functions can be rewritten as follows:

$$\ell\left(z_k^l\middle|H_{k1}^l,A_k\right) = \frac{2b^{\upsilon}z_k^l}{\Gamma(\upsilon)}\int_0^{\infty}\frac{\eta^{\upsilon-1}}{\eta+{A_k}^2}\exp\left[-\frac{{z_k^l}^2}{\eta+{A_k}^2}-b\eta\right]\mathrm{d}\eta, \tag{7}$$

$$\ell\left(z_k^l\middle|H_{k0}^l\right) = \frac{4\sqrt{b}^{\upsilon+1}{z_k^l}^{\upsilon}}{\Gamma(\upsilon)}\kappa_{\upsilon-1}\left(2\sqrt{b}z_k^l\right), \tag{8}$$

where $\kappa_n(\cdot)$ denotes the modified Bessel function of the second kind.

The final recursion update is as follows:

$$p\left(H_{k1}^l,A_k\middle|z_k^l\right) = \frac{\ell\left(z_k^l\middle|H_{k1}^l,A_k\right)p\left(H_{k1}^l,A_k\right)}{\int\ell\left(z_k^l\middle|H_{k1}^l,A_k\right)p\left(H_{k1}^l,A_k\right)\mathrm{d}A_k+\ell\left(z_k^l\middle|H_{k0}^l\right)p\left(H_{k0}^l\right)} \tag{9}$$

where $p\left(H_{k0}^l\right)$ can be obtained by directly setting A_k equal to zero in $p\left(H_{k1}^l,A_k\right)$.

2.2 Clutter parameter estimation

Generally, clutter estimation methods include the maximum likelihood (ML) [17], moments [12], expectation-maximization (EM), higher-order and fractional moments [18], and Bayesian approach [19]. All the methods above are not suitable for scenes with multiple targets and nonstationary clutter. Therefore, a new parameter estimation method is put forward, which can achieve minimax optimal model. Its essence is to regard nonstationary sea clutter as piecewise stationary series.

In the first stage, kernel density estimation (KDE) via diffusion is applied, in which semilinear parabolic partial differential equation (PDE) is chosen because it is suitable for smoothing heavy-tailed clutter [20,21]. The KDE uses an adaptive kernel density estimation method based on the smoothing properties of linear diffusion processes. It views the estimation kernel as the transition density of a diffusion process. On the assumption that the measurement samples are stationary, we use all samples to get the first estimated result. Then, we move one sample forward and on the same assumption get another estimated result. The recursive estimation is repeated until no samples are left.

In the second stage, the obtained estimations go through a mixture process as

$$\hat{f}_l = \sum_{m=1}^{N}\gamma_l^m\hat{f}_l^m \tag{10}$$

where γ_l^m is the mixture weight of individual estimation, N is the number of samples, and $\hat{f}_l^m$ is the estimation result of the first stage [22]. Here the time index k is omitted for simplicity. The weights are also in normalized version,

$$\gamma_l^m = \frac{\hat{\gamma}_l^m}{\sum\limits_{m=1}^{N} \hat{\gamma}_l^m}. \tag{11}$$

The mixture weights can be updated recursively as

$$\hat{\gamma}_l^m = \begin{cases} \dfrac{N-m}{N-m+1} \hat{\gamma}_{l-1}^m \hat{f}_{l-1}^m, m<0 \\ \sum\limits_{m=1}^{N} \dfrac{1}{N-m+1} \hat{\gamma}_{l-1}^m \hat{f}_{l-1}^m, m=N \end{cases}. \tag{12}$$

Finally, the parameters of clutter distribution are calculated from the estimated probability density function. Let $\hat{z}_k^1, \hat{z}_k^2, \cdots, \hat{z}_k^{l_{stat}}$ be samples from the piecewise stationary sea clutter, which are generated by the estimated probability density function. The first and second sample moments are estimated as

$$\hat{m}_1 = \frac{1}{l_{\rm stat}} \sum_{l=1}^{l_{stat}} \hat{z}_k^1, \tag{13}$$

$$\hat{m}_2 = \frac{1}{l_{\rm stat}} \sum_{l=1}^{l_{stat}} \hat{z}_k^{l\,2}, \tag{14}$$

where $l_{\rm stat}$ denotes the length of the stationary measurements, which is not a changing parameter and depends on the result of clutter parameter estimation.

Then, the shape parameter is given by

$$v = \frac{1}{4}\left[\ln\left(\frac{\pi \hat{m}_2}{4\hat{m}_1^2}\right)\right]^{-1}. \tag{15}$$

The scale parameter is given by

$$b = \frac{\hat{m}_2}{v}. \tag{16}$$

The principle of clutter parameter estimation is illustrated in Fig. 1.

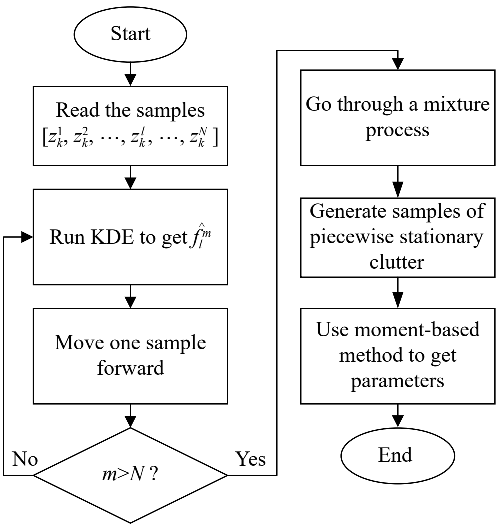


Fig. 1 Principle of clutter parameter estimation

2.3 Closely spaced targets detection

When there are more than one target in a single measurement cell, the targets in the same measurement cell can be treated as a cluster. After parameter estimation, the sum contribution of all targets in the same measurement cell can be obtained. If two targets in the cell are assumed in the test, of which one is considered as clutter, the target parameters can be revised [14] as follows:

$$\sqrt{b'} = \sqrt{b} + \frac{\Gamma(\upsilon)}{\Gamma(1.5)\Gamma(\upsilon+0.5)} A_k^2. \tag{17}$$

The likelihood functions (7) and (8) can be rewritten as

$$\ell\left(z_k^l \middle| H_{k1}^l, A_k\right) = \frac{2b'^{\upsilon} z_k^l}{\Gamma(\upsilon)} \int_0^{\infty} \frac{\eta^{\upsilon-1}}{\eta + A_k^2} \exp\left[-\frac{z_k^{l\,2}}{\eta+A_k^2} - b'\eta\right] {\rm d}\eta, \tag{18}$$

$$\ell\left(z_k^l \middle| H_{k0}^l\right) = \frac{4\sqrt{b'}^{\upsilon+1} z_k^{l\,\upsilon}}{\Gamma(\upsilon)} K_{\upsilon-1}\left(2\sqrt{b'} z_k^l\right). \tag{19}$$

If the detection condition is satisfied, a detection is declared. Then, the contribution of the detected target is deleted from the cell measurement. This process is repeated until the detection condition is not satisfied. This study focuses on detection instead of tracking, so it is not necessary to discriminate targets in the same measurement cell. Fig. 2 is the illustration of the principle.

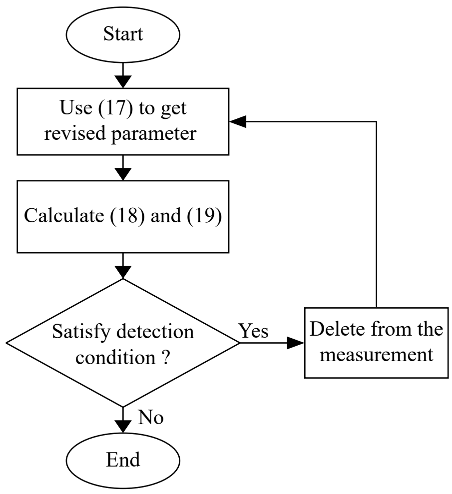


Fig. 2 Principle of closely spaced targets detection

2.4 Proposed algorithm

Adaptive detection threshold which is related to the estimated clutter density is adopted. For every stationary piece of the clutter measurements, one-sample Kolmogorov-Smirnov test (KS test) is applied to compare the distance between measurements and the series obtained by clutter estimated density. Define a logistic function as

$$\ell = \lg\left(1+\exp\left(D_s^l z_k^l\right)\right) \tag{20}$$

where D_s^l refers to the result of KS test of cell l. Then, the detection threshold is proportional to L given as

$$T = \sum_{n=1}^{l_{\text{stat}}} z_k^n + \alpha L \tag{21}$$

where

$$L = \sum_{n=1}^{l_{\text{stat}}} \ell. \tag{22}$$

α is a predefined scale, which is determined by

$$\alpha = \frac{1}{2}\min\left(\exp(-R), \frac{1+\exp(-R)}{4R}\right) \tag{23}$$

where R is the diameter of the sample set [22].

After applying detection threshold T, we calculate the final detection threshold used in the proposed algorithm T_{final} which represents the percentage of samples larger than T.

The final detection criterion is defined as

$$\begin{cases} p\left(H_{k1}^l, A_k \middle| z_k^l\right) \geqslant T_{\text{final}} \Rightarrow H_1 \\ p\left(H_{k1}^l, A_k \middle| z_k^l\right) < T_{\text{final}} \Rightarrow H_0 \end{cases}. \tag{24}$$

The processing steps of the proposed algorithm are listed in Algorithm 1.

Algorithm 1 Processing steps of the proposed Bayesian TBD algorithm

Step 1 Assign prior distributions for $p\left(H_{k1}^l, A_k\right)$ and $p\left(H_{k0}^l\right)$.

Step 2 Obtain the measurements of each cell.

Step 3 Use clutter parameter estimation to get parameters b and v.

Step 4 Use (17) to obtain parameter b'.

Step 5 Compute the likelihood functions by (18) and (19).

Step 6 Compute the joint probability distribution function (PDF) by (9).

Step 7 If a target is detected, delete it from the cell under test.

Step 8 Repeat Steps 3–7 until the detection condition is not satisfied.

Step 9 Calculate (4) to advance to the next time step.

Step 10 Go back to Step 2.

3. Simulation results

Experimental data are taken from a program called "a data-sharing program for sea-detecting radar" conducted by Naval Aviation University [23]. The experimental parameters are given in Table 1. The raw clutter map is shown in Fig. 3.

Table 1 Experimental parameters

Parameter	Value
T_X frequency	X-band
Range resolution/m	6
Pulse repetition/kHz	3
Range distance/m	3 577.5–4 572.5 (about 166 gates)
Duration/s	2

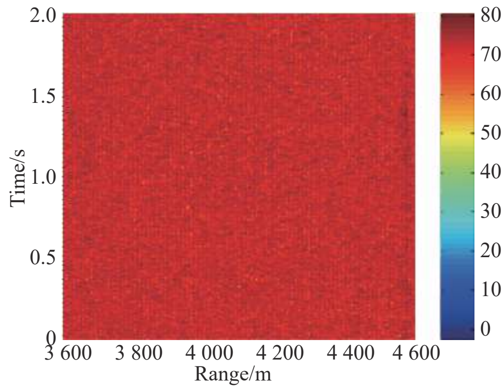


Fig. 3 Measured clutter amplitude

Since the range sampling interval is nearly equal to the range resolution, the measured clutter map is used instead of further decimation. Several synthetic Swerling 0 targets are embedded into the clutter measurements.

Simulation analysis mainly includes three parts. In the first part, different clutter parameter estimation methods are integrated in the TBD algorithm with predefined detection threshold of 0.7 in order to prove the superiority of the proposed clutter parameter estimation method. In the second part, the proposed parameter estimation method is integrated in the TBD algorithm with adaptive detection thresholds in order to verify the efficiency of closely spaced target detection. In the third part, different detection methods are testified in detecting small targets in nonstationary sea clutter in order to show the usefulness of the proposed detection algorithm.

Part 1 In order to study the influence of the parameter estimation method on the detection performance, the ML estimation is compared with the new clutter parameter estimation method. It is supposed that there exist three Swerling 0 targets whose velocity, location, emergency time, and signal-to-clutter ratio (SCR) parameters are shown in Table 2.

Table 2 Target parameters

Target	Velocity/(m·s^{-1})	Location/m	Emergence time/s	SCR/dB
Target 1	100	3 677.5	0.5	2
Target 2	100	4 077.5	1	2
Target 3	100	4 277.5	1.5	2

The results are shown in Fig. 4 and Fig. 5. The performance of the detection method based on the new clutter parameter estimation method is better than that of the detection method based on the ML estimation. This is because the new clutter parameter estimation method could handle shortage of samples and the influence of outliers.

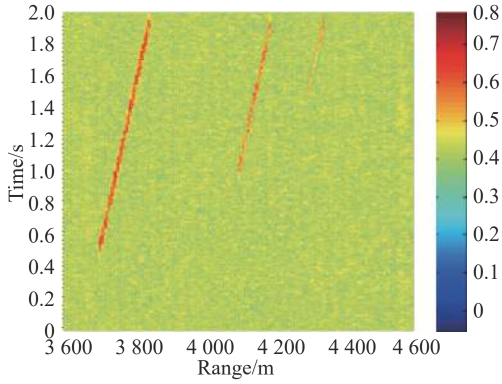


Fig. 4 Results of the proposed method

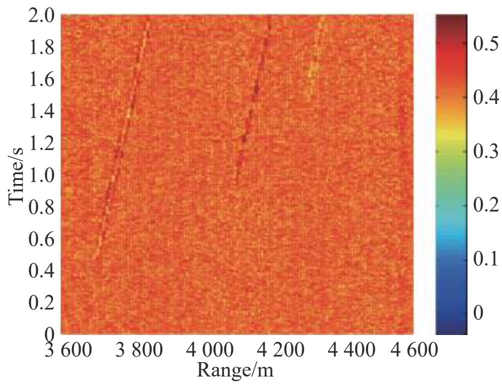


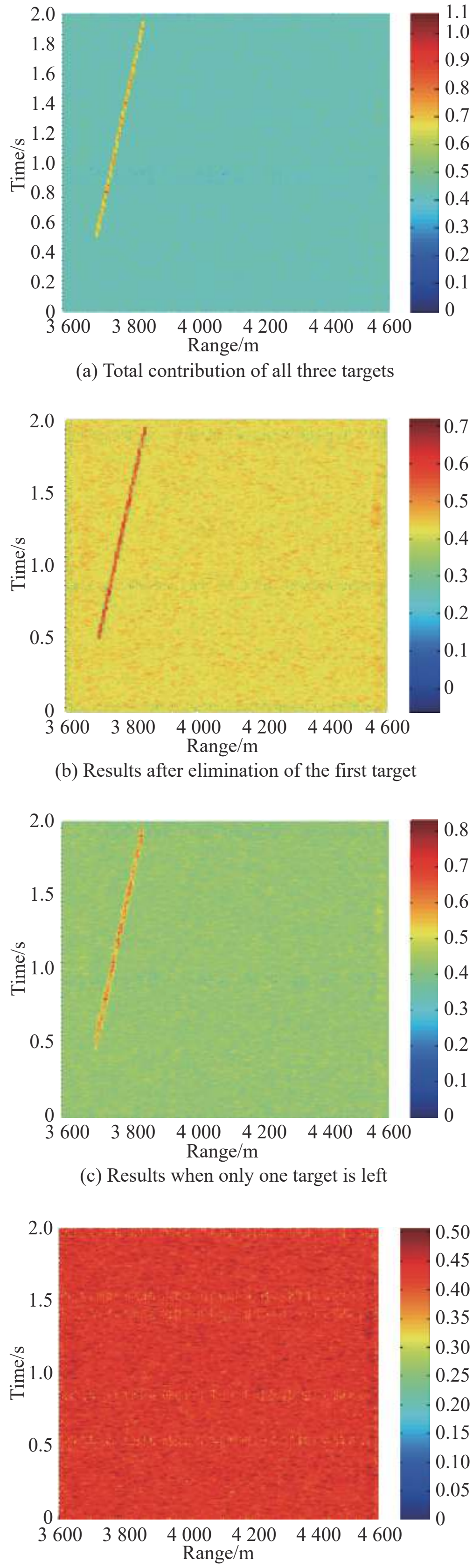
Fig. 5 Results of Bayesian TBD using ML estimation

Part 2 The detection performance of the proposed algorithm is studied for multiple closely spaced targets. The target parameters are shown in Table 3. The results of the proposed algorithm are shown in Fig. 6(a)–Fig. 6(d).

Table 3 Closely spaced target parameters

Target	Velocity/$(\mathrm{m \cdot s^{-1}})$	Location/m	Emergence time/s	SCR/dB
Target 1	100	3 677.5	0.5	2
Target 2	100	3 677.5	0.5	2
Target 3	100	3 677.5	0.5	2

The total contribution of all three targets is presented in Fig. 6(a). The contribution of the two targets after the elimination of the first one is displayed in Fig. 6(b). Finally, the contribution of one target after the elimination of the other two is shown in Fig. 6(c). All three targets can be detected by the proposed algorithm.



(a) Total contribution of all three targets

(b) Results after elimination of the first target

(c) Results when only one target is left

(d) Results when no target is left

Fig. 6 Proposed algorithm performance for closely spaced targets

From Fig. 6(d), it is clear that when no target is left, there is no false alarm. This proves that the proposed algorithm can reduce the false alarms.

Part 3 We compare different detection methods, including the proposed algorithm, the proposed algorithm with fixed detection threshold of 0.7 and TBD with clutter parameter estimation based on the changepoint algorithm at different SCR values, namely, at SCR of 4 dB, 2 dB, −2 dB, −4 dB, and −6 dB. It should be noted that the clutter parameter estimation method based on the changepoint algorithm also regards the nonstationary measurements to be piecewise stationary series. The target parameters are the same as those in Part 1 except for SCR values. The results are shown in Fig. 7.

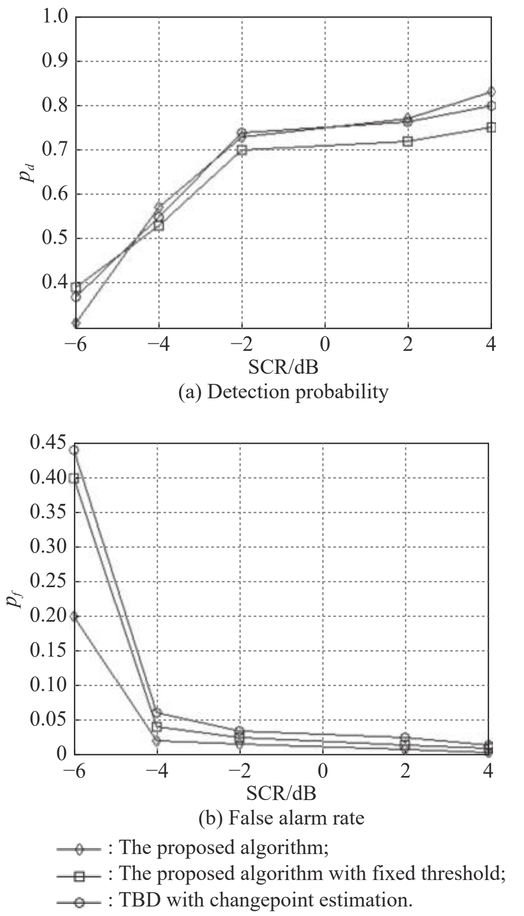


Fig. 7 Performance comparison between different detection methods at different SCRs

The results confirm that both the proposed algorithm and TBD with clutter parameter estimation method based on the change point algorithm have better detection performance than the proposed algorithm with fixed detection threshold. Also, the proposed algorithm displays better performance in reducing false alarms than the other two algorithms. This is mainly because the proposed algorithm can adaptively adjust the detection threshold according to the difference between received measurements and sea clutter.

4. Conclusions

This study proposes a new Bayesian TBD filter to detect small closely-spaced targets in nonstationary sea clutter. It can be easily implemented with an adaptive threshold and uses a new parameter estimation method to track the changes of sea clutter. We evaluate our proposed method on real-world data sets. Simulation results show that the proposed algorithm can improve detection probability and reduce false alarm to a certain extent. Future work will apply sensor networks to deal with the detection of small targets in nonstationary sea clutter.

References

[1] ROSENBERG L, VENKATARAMAN K, JENKE C. Target detection in medium grazing angle sea clutter using scan to scan processing. Proc of the International Radar Conference, 2019. DOI: 10.1109/RADARA1533.2019.171341.

[2] ZHANG Y S, WANG W G, WANG N, et al. A knowledge-aided wald detector for target detection in sea clutter. Proc. of the International Conference on Control, Automation and Information Sciences, 2019: 1–4.

[3] CHEN S C, LUO F, LUO X X. Multiview feature-based sea surface small target detection in short observation time. IEEE Geoscience and Remote Sensing Letters, 2020: 1–5.

[4] ROSENBERG L, DUK V, NG B. Detection in sea clutter using sparse signal separation. IEEE Trans. on Aerospace and Electronic Systems, 2020: 1–11.

[5] ZAIMBASHI A, DERAKHTIAN M, SHEIKHI A. Invariant target detection in multiband FM-based passive bistatic radar. IEEE Trans. on Aerospace and Electronic Systems, 2014, 50(1): 720–736.

[6] ZAIMBASHI A. Forward M-ary hypothesis testing based detection approach for passive radar. IEEE Trans. on Signal Processing, 2017, 65(10): 2659–2671.

[7] SOLATZADEH Z, ZAIMBASHI A. Accelerating target detection in passive radar sensors: delay-doppler-acceleration estimation. IEEE Sensors Journal, 2018, 18(13): 5445–5454.

[8] BOLVARDI H, DERAKHTIAN M, SHEIKHI A. Dynamic clutter suppression and multitarget detection in a DVB-T-based passive radar. IEEE Trans. on Aerospace and Electronic Systems, 2017, 53(4): 1812–1825.

[9] SANTI F, PASTINA D. Application of track-before-detect techniques in GNSS-based passive radar for maritime surveillance. Proc. of the IEEE Radar Conference, 2019: 1–6.

[10] GUERRAOU Z, KHENCHAF A, COMBLET F, et al. Particle filter track-before-detect for target detection and tracking from marine radar data. Proc. of the IEEE Conference on Antenna Measurements & Applications, 2019: 1–4.

[11] RISTIC B, ROSENBERG L, KIM D Y, et al. Bernoulli track-before-detect filter for maritime radar. IET Radar, Sonar &

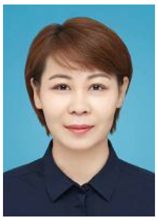
Navigation, 2020, 14(3): 356–363.
[12] KIM D Y, RISTIC B, WANG X, et al. A comparative study of track-before-detect algorithms in radar sea clutter. Proc. of the International Radar Conference, 2019. DOI: 10.1109/RADAR41533.2019.171306.
[13] RISTIC B, ROSENBERG L, KIM D Y, et al. Benourlli filter for track-before-detect: swerling-1 target inK-distributed clutter. Proc. of the International Radar Conference, 2019. DOI: 10.1109/RADAR41533.2019.171217.
[14] RISTIC B, KIM D Y, ROSENBERG L, et al. Bernoulli multitarget track-before-detect for maritime radar. Proc. of the IEEE International Radar Conference, 2020: 878–883.
[15] BERRY P, VENKATARAMAN K, ROSENBERG L. Adaptive detection of low-observable targets in correlated sea clutter using Bayesian track-before-detect. Proc. of the IEEE Radar Conference, 2017: 0398–0403.
[16] STONE D L, STREIT R L, CORWIN T L. Bayesian multiple target tracking. London: Artech House, 2014.
[17] BREKKE E, KIRUBARAJAN T, THARMARASA R. Tracking dim targets using integrated clutter estimation. Proceedings of the SPIE, 2007, 6699: 669905.
[18] NORTHROP J A, PAPANDREOU-SUPPAPPOLA A. Computationally efficient estimation of compound K-distribution sea clutter in thermal noise and its application to sea echo reflectivity observations. IEEE Trans. on Aerospace and Electronic Systems, 2020, 56(3): 2340–2350.
[19] CHEN X, THARMARASA R, PELLETIER M, et al. Integrated bayesian clutter estimation with JIPDA/MHT trackers. IEEE Trans. on Aerospace and Electronic Systems, 2013, 49(1): 395–414.
[20] MAJDARA A, NOOSHABADI S. Nonparametric density estimation using copula transform, Bayesian sequential partitioning, and diffusion-based kernel estimator. IEEE Trans. on Knowledge and Data Engineering, 2020, 32(4): 821–826.
[21] BOTEV Z I, GROTOWSKI J F, KROESE D P. Kernel density estimation via diffusion. The Annals of Statistics, 2010, 38(5): 2916–2957.
[22] GOKCESU K, KOZAT S S. Online anomaly detection with minimax optimal density estimation in nonstationary environments. IEEE Trans. on Signal Processing, 2018, 66(5): 1213–1227.
[23] LIU N B, DONG Y L, WANG G Q, et al. Sea-detecting X-band radar and data acquisition program. Journal of Radars, 2019, 8(5): 656–667. (in Chinese)

Biographies

XU Cong was born in 1983. She received her B.S. and Ph.D. degrees in communication and information system from Harbin Engineering University, Harbin, in 2006, and 2010, respectively. She is now engaged in post doctoral work in signal and information processing with the Department of Information and Communication, University of Electronic Science and Technology of China. Her research interests are radar weak signal detection and radar target tracking.
E-mail: xucong_0803@126.com

HE Zishu was born in 1962. He received his B.S., M.S., and Ph.D. degrees in signal and information processing from University of Electronic Science and Technology of China (UESTC), Chengdu, in 1984, 1988, and 2000, respectively. He is a professor in signal and information processing with the Department of Information and Communication, UESTC. His research interests involve array signal processing, digital beamforming, the theory on MIMO communication and MIMO radar, adaptive signal processing, and channel estimation. He has published more than 100 articles and two books on signals and systems and modern digital signal processing and its applications.
E-mail: zshe@uestc.edu.cn

LIU Haicheng was born in 1979. He received his B.S degree in Electronic Information Engineering from Northeast Agricultural University, Harbin, in 2003 and M.S degree in Electronic and Communication Engineering from Harbin Institute of Technology, Harbin, in 2012. He is now working with the Depatment of Electrical and Information Engineering in Heilongjiang Institute of Engineering. His research interests are signal processing and intelligent hardware.
E-mail: liuhaicheng@126.com



LI Yadan was born in 1985. She received her double B.S. degrees in business administration and radar communication from Civil Aviation University of China in 2008. She received her M.S. degree in business administration from University of Chinese Academy of Sciences in 2020. She is now engaged in air traffic controll in Air Traffic Management Bureau of China Civilaviation Administration. Her research interests are radar signal detection, communication navigation, and air traffic control system construction.
E-mail: Liyadan@163.com